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A Review on Integrated Artificial Intelligence Approaches for Sustainable Aquaculture

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Abstract

As the aquaculture industry continues to expand, there is an increasing need to adopt modern tools to enhance productivity, sustainability, and decision-making. AI technologies are at the forefront of this transformation, offering solutions such as automation of tasks like water quality monitoring, feeding schedules, and disease detection, leading to improved operational efficiency and fish health. AI also aids in early disease detection and supports precision aquaculture by adjusting environmental variables like feeding and oxygen levels to optimize fish growth. However, the adoption of AI comes with challenges. The availability of quality data, the need for domain-specific datasets, and the complexity of AI models can hinder progress. High initial costs and infrastructure demands present obstacles for small-scale farmers. Ethical considerations, such as data privacy and responsible use of AI, also need careful attention. This article reviews the benefits and challenges of AI in aquaculture, highlighting the importance of adopting modern tools as the industry evolves and the barriers that must be addressed for successful implementation. It also discusses how AI can contribute to sustainable practices, improving efficiency while reducing environmental impact, and highlights the potential for AI to shape the future of aquaculture management.

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Introduction

The global aquaculture and fishery industry is a vital sector, valued at USD 281.5 billion and producing 122.6 million tons of aquatic products in 2020 alone. Asia continues to be the leading producer, contributing nearly 91.6% of the world's total aquaculture output. As global demand for aquatic products increases, driven by population growth, rising incomes, and a growing awareness of the health benefits of fish, the industry is expected to grow by an additional 14% by 2030 (FAO, 2022). Fish and fisheries products, particularly those rich in long-chain polyunsaturated fatty acids (LCPUFAs), are increasingly recognized for their superior nutritional value compared to terrestrial animal proteins, offering essential nutrients and contributing to improved food security (Beveridge et al., 2013). While the aquaculture industry is growing rapidly, this expansion brings with it a set of challenges. There is a pressing need to optimize fish growth, ensure the health of farmed fish populations, manage water quality, and address the risks posed by disease outbreaks, all while ensuring the availability of quality broodstock and fingerlings (Michael H, 2019). However, traditional methods of managing these factors are increasingly inadequate. These methods generally rely on manual observations and periodic data collection, which are prone to human error, lack real-time data, and are labor-intensive. As aquaculture operations scale up, these methods become less effective, unable to cope with the increasing complexity and speed required to manage modern farming practices.

To address these challenges, there is a clear need for innovative technologies that can provide more efficient, data-driven, and scalable solutions. This is where Artificial Intelligence (AI) can play a transformative role. AI refers to the development of computer systems that are capable of performing tasks typically requiring human intelligence, such as learning from data, problem-solving, and decision-making (Dellermann *et al*., 2019). In aquaculture, AI technologies provide the opportunity to optimize fish growth, monitor fish health, and improve overall farm management by providing real-time data, predictive analytics, and decision support systems. By analyzing large datasets and historical information, AI can adjust practices such as feeding management, water quality monitoring, and environmental control, leading to more efficient resource use and better growth performance (Bagheri *et al*., 2019). One of the key advantages of AI in aquaculture is its potential to monitor the health of farmed fish populations. Disease outbreaks are a major risk to aquaculture, leading to significant economic losses and environmental harm (Abdelrahman *et al*., 2023). Traditional monitoring systems often fail to detect diseases at an early stage, which can allow infections to spread rapidly and cause widespread damage. AI-driven solutions, such as early warning systems and disease detection algorithms, can detect signs of illness or abnormal behavior much earlier, allowing for prompt intervention. By using techniques such as machine learning, AI systems can continuously learn from data and improve their predictive capabilities, enabling early identification of potential health issues (MacIntyre *et al*., 2023; Yue & Shen, 2022). This timely detection can significantly reduce the spread of disease, enhancing the overall sustainability of aquaculture operations. Furthermore, AI has the potential to optimize various aspects of farm management, including feeding practices and environmental monitoring. Machine learning algorithms, for example, can process large datasets to identify patterns in fish growth, feed consumption, and water quality, leading to more accurate predictions of future needs. Genetic algorithms, a type of AI, can optimize feed compositions, feeding schedules, and environmental conditions to maximize fish growth while minimizing waste (Luna *et al*., 2019). Deep learning, a subset of machine learning, has proven effective in tasks such as computer vision, which is particularly useful for detecting physical signs of disease or injury in fish populations. Through these AI-driven technologies, aquaculture operations can improve efficiency, reduce waste, and increase profitability, all while reducing their environmental impact.

Artificial Intelligence (AI) in Aquaculture

Artificial Intelligence (AI) is revolutionizing aquaculture by enhancing productivity, sustainability, and the overall efficiency of fish farming. AI is being integrated into various aquaculture processes, including optimizing feed management, monitoring water quality, identifying diseases, and forecasting market trends. According to Prapti *et al*., 2022, AI not only supports fish growth but also lowers operational costs, improves animal welfare, and reduces the environmental footprint of fish farming. As AI technology advances, its potential for transforming aquaculture becomes increasingly significant. AI systems replicate cognitive functions such as learning, reasoning, and problem-solving, making them invaluable across industries like healthcare, agriculture, and aquaculture (Bagde & Pathan, 2023)

Environmental Surveillance through AI in Aquaculture

AI algorithms can be applied to analyze data gathered from various sensors used in aquaculture systems to monitor water quality parameters such as temperature, pH, dissolved oxygen levels, ammonia concentration, and turbidity. These parameters play a critical role in maintaining a healthy environment for fish. By utilizing machine learning models, patterns and anomalies in sensor readings can be detected, providing early alerts for potential environmental problems that could harm fish health. Early detection of such issues allows farmers to take corrective actions before any significant damage occurs, minimizing the risk to the fish and ensuring optimal environmental conditions for growth.

a. Sensor Data Analysis

Real-time sensor data, such as temperature, pH, dissolved oxygen, ammonia, nitrate, and turbidity, is vital for maintaining a healthy aquatic environment. AI algorithms analyze this data to detect deviations from ideal conditions. By employing anomaly detection or pattern recognition, these systems identify unusual readings that may indicate a problem with water quality. AI can also train machine learning models using historical water quality data to create predictive models that estimate future values of key parameters based on trends and influencing factors (Wang *et al*., 2021). This predictive capability enables farmers to anticipate and mitigate potential issues before they escalate.

b. Image and Video Analysis

AI-driven image and video analysis techniques, such as computer vision, can process footage from cameras installed in fish tanks or ponds. These models are designed to recognize patterns in fish behavior, detect signs of stress, disease, or other health issues, and monitor feeding activities. For instance, an AI system can automatically detect unusual fish movements, reduced feeding, or visible signs of disease. Moreover, image analysis can be employed for automatic fish counting and size estimation, offering vital data for

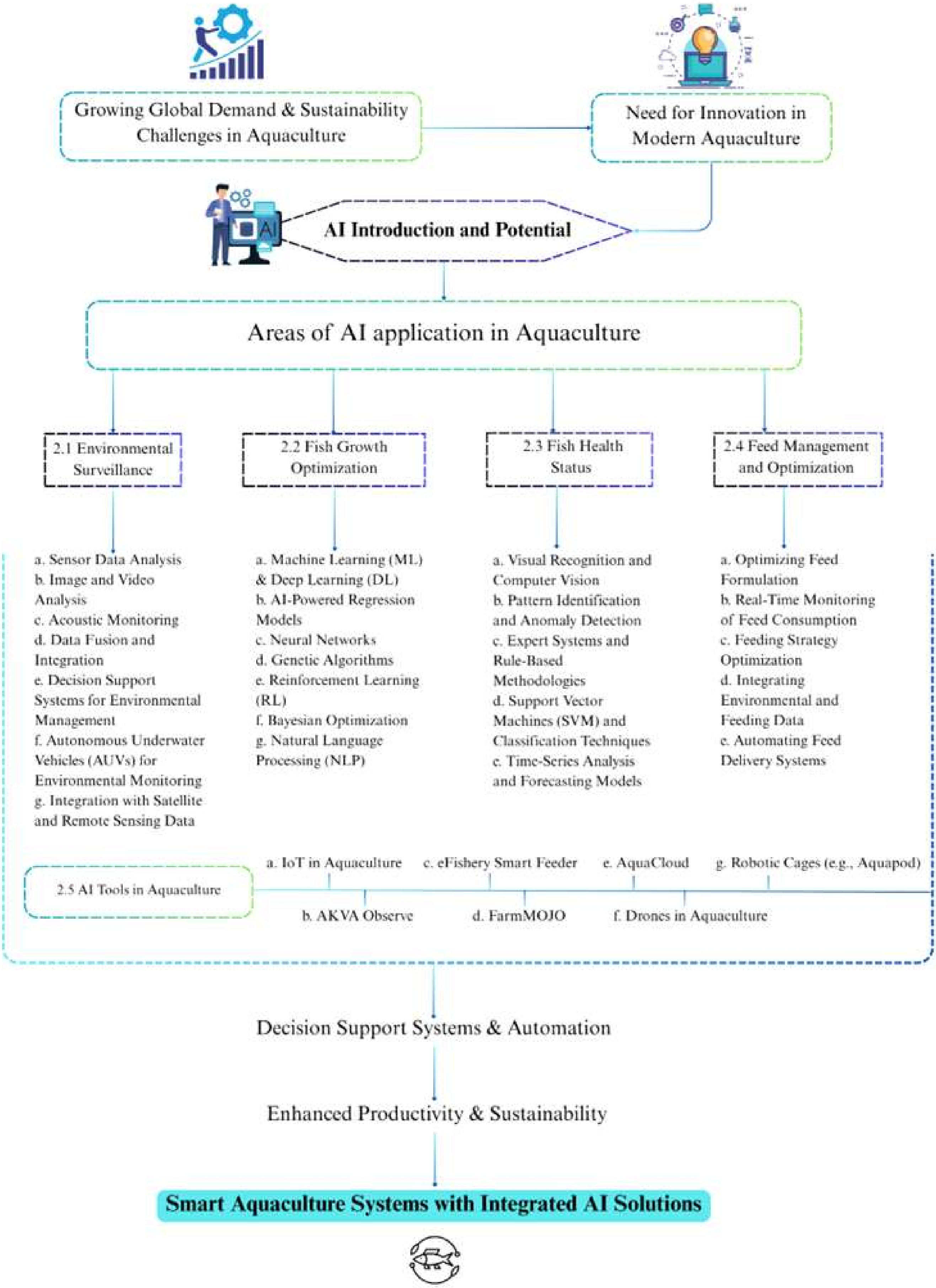

Fig 1. Conceptual Framework of AI Integration in Key Functional Areas of Aquaculture"

effective population management and improving overall farm efficiency. By automating these tasks, AI reduces the manual labor involved in health monitoring and provides more accurate, real-time insights.

c. Acoustic Monitoring

AI algorithms can also be utilized to analyze underwater acoustic data, which is often employed to observe fish behavior, migration patterns, and communication signals. By using acoustic monitoring techniques, farmers can evaluate fish populations, pinpoint spawning areas, and identify any unusual behaviors or environmental disturbances that might indicate potential problems. For example, AI can be used to track the sounds of fish schools, detect the presence of predators, or assess fish health through their vocalizations or movement patterns. Acoustic monitoring offers an unobtrusive way to observe fish and their environment, contributing valuable insights into their well-being.

d. Data Fusion and Integration

Environmental monitoring typically involves the collection of data from various sources, including sensors, weather stations, and satellite imagery. AI techniques excel in combining and analyzing these diverse datasets to offer a holistic understanding of the fish habitat. By integrating data from different sources, AI can provide insights into how environmental factors such as water temperature, weather conditions, and water quality influence fish behavior, growth, and health. Machine learning models can analyze historical environmental data alongside fish growth and health records to create predictive models. These models can anticipate future environmental conditions, forecast potential disease outbreaks, and suggest optimal strategies for feed and water management to enhance fish growth (Gladju *et al.*, 2022). Predictive capabilities of AI can help farmers take proactive measures, improving sustainability and productivity.

e. Decision Support Systems for Environmental Management

AI-powered decision support systems for environmental management leverage real-time data, historical records, and predictive models to assist farmers in making optimal management decisions. These systems can recommend actions like adjusting feeding rates, changing water flow, or initiating interventions based on the current environmental conditions and observed fish health indicators. By utilizing AI, these systems provide farmers with actionable insights that help maintain a balanced and healthy environment, minimizing the risk of disease and maximizing growth potential (Panudju *et al.*, 2023).

f. Autonomous Underwater Vehicles (AUVs) for Environmental Monitoring

AI can be integrated into autonomous underwater vehicles (AUVs), enabling them to navigate and gather environmental data in remote or hazardous locations. AUVs equipped with sensors and cameras can monitor water quality parameters, observe fish behavior, and collect data in real time. These AI-powered vehicles can operate autonomously, allowing them to gather valuable data from hard-to-reach areas. AI algorithms process the collected data on-site, relaying it back to monitoring systems for further analysis (Ubina *et al.*, 2022). AUVs are already among the most commonly used AI-driven systems in aquaculture, with capabilities for continuous monitoring of environmental conditions in large fish farms.

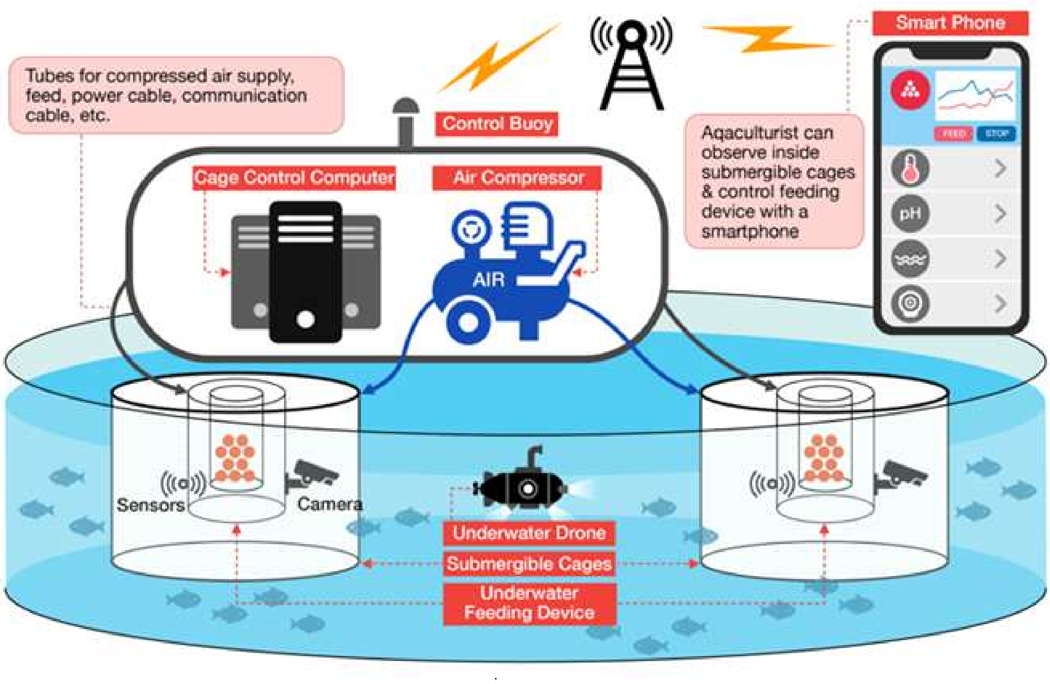

Fig. 2 A Smart Aquaculture Syst

(Source: Vo et al., 2021)em in action, utilizing AI, IoT, and real-time data monitoring to optimize fish farming conditions

g. Integration with Satellite and Remote Sensing Data

AI is also capable of integrating satellite remote sensing data with real-time on-site sensor data to gather comprehensive information about the water environment. For example, a system that combines data on water depth, turbidity, temperature, pH, nitrate levels, and chlorophyll concentrations, can provide an in-depth understanding of water quality and fish health. By merging satellite data with sensor readings from aquaculture systems, AI can offer geospatial insights that help farmers monitor environmental trends over large areas. This integration allows for more accurate assessment and better resource management, reducing environmental risks associated with fish farming.

AI Techniques in Aquaculture and Fish Growth Optimization

AI has revolutionized aquaculture by offering innovative solutions to enhance fish growth, optimize resources, and improve overall farm management. By analyzing complex datasets and predicting outcomes, AI techniques address key challenges like feeding efficiency, water quality management, and disease control, resulting in sustainable and profitable practices (Wang *et al.*, 2021). Below is a detailed overview of AI methodologies applied in aquaculture:

a. Machine Learning (ML) & Deep Learning (DL)

Machine Learning (ML) and Deep Learning (DL) are powerful AI tools for aquaculture systems. ML techniques analyze large datasets to create predictive models for growth optimization, feeding schedules, and environmental monitoring. Supervised learning can predict fish weight or health conditions based on labeled datasets, while unsupervised learning helps categorize fish behavior or detect anomalies. Reinforcement learning is particularly useful in dynamic systems, such as real-time feeding adjustments. Deep Learning, a subset of ML, uses neural networks with multiple layers to analyze unstructured data like images or videos. This is especially beneficial for monitoring fish health, identifying stress-related behaviors, or detecting diseases. For example, convolutional neural networks (CNNs) can identify infections through image analysis, while recurrent neural networks (RNNs) track growth trends over time. These methods collectively enhance operational efficiency and fish welfare (Sahoo *et al.*, 2020).

b. AI-Powered Regression Models

AI-driven regression models provide detailed insights into the relationship between variables like water quality, feed type, and environmental conditions, and their impact on fish growth. Multivariate regression models account for interactions among several factors, offering a comprehensive understanding of growth dynamics. Non-linear models capture complex growth patterns influenced by variable environmental conditions, while ensemble models like random forests combine multiple algorithms to improve prediction accuracy. These models enable farmers to design optimized feeding strategies, identify growth-limiting factors, and implement resource-efficient practices. By predicting outcomes under various scenarios, regression models reduce trial-and-error efforts, saving time and resources while ensuring sustainability (Wu *et al.*, 2021).

c. Neural Networks

Neural networks excel in processing large-scale and complex aquaculture datasets. These AI systems are adept at recognizing patterns, making them invaluable for analyzing feed efficiency, environmental conditions, and fish health. For instance, CNNs are extensively used for image analysis to detect diseases, evaluate fish size, or monitor swimming patterns. These networks offer precision in identifying early-stage infections or abnormalities that are challenging to detect visually. Advanced neural network techniques like generative adversarial networks (GANs) simulate various environmental conditions, helping aquaculture managers predict fish responses to temperature changes or water quality shifts. This enables proactive interventions to ensure optimal growth and health outcomes (Kaur *et al.*, 2023b).

d. Genetic Algorithms

Genetic Algorithms (GAs) mimic evolutionary processes to find optimal solutions for aquaculture challenges. They refine feeding schedules, stocking densities, and environmental conditions through iterative processes of selection, crossover, and mutation. For instance, GAs can identify the most efficient feeding strategies to maximize growth while minimizing waste. Additionally, GAs aid in selective breeding programs by optimizing genetic traits such as disease resistance, growth rates, and environmental adaptability. By streamlining these processes, GAs reduces reliance on manual experiments, leading to faster and more accurate results in improving aquaculture systems (Albadr *et al.*, 2020).

e. Reinforcement Learning (RL)

Reinforcement Learning (RL) offers an adaptive approach to decision-making in aquaculture systems. RL agents learn by interacting with their environment, and continuously improving their strategies based on rewards or feedback. In fish farming, RL is used to optimize feeding strategies by analyzing real-time data on water temperature, oxygen levels, and fish behavior. RL also powers autonomous systems like drones and underwater robots for monitoring and surveillance. These systems adapt to changing conditions, improving efficiency in tasks like disease detection and water quality assessment. By integrating RL with IoT devices, aquaculture systems can achieve high levels of automation and precision (Aljehani *et al.*, 2023).

f. *Bayesian Optimization*

Bayesian Optimization is a probabilistic technique used to fine-tune aquaculture parameters. Unlike traditional trial-and-error methods, it uses a surrogate model to predict outcomes and iteratively explores the parameter space to find optimal conditions. This is particularly useful for managing variables like temperature, salinity, and stocking densities in complex systems. For example, Bayesian optimization can identify the best combinations of water quality parameters for different species or simulate growth outcomes under varying environmental conditions. It ensures efficient resource use and adaptability in dynamic scenarios, making it a valuable tool for aquaculture practitioners (Zaki *et al.,* 2023).

g. *Natural Language Processing (NLP)*

Natural Language Processing (NLP) enhances decision-making and communication in aquaculture. By processing textual data from manuals, reports, or research papers, NLP systems extract actionable insights to improve farm management practices. Chatbots powered by NLP provide real-time assistance to farmers, offering guidance on feeding schedules, water quality, and disease prevention. NLP also improves stakeholder communication by analyzing feedback from farmers, suppliers, and policymakers. Sentiment analysis tools assess perceptions about aquaculture practices, helping managers address concerns and foster collaboration. By translating complex data into easily understandable recommendations, NLP bridges the gap between advanced AI systems and end-users.

AI Methods for Monitoring Fish Health Status (Disease Detection and Diagnosis)

AI techniques play a crucial role in the monitoring of fish health and disease detection within aquaculture systems. These advanced methods use various data sources, such as images, videos, water quality parameters, and fish behavior, to identify disease symptoms, stress indicators, and behavioral changes in fish populations. The ability to automate these processes enhances the efficiency and accuracy of health monitoring, enabling early detection and management of diseases, thus ensuring better fish health and overall productivity.

a. *Visual Recognition and Computer Vision*

Fish diseases often manifest through visible symptoms on the fish's body, such as lesions, discoloration, and unusual behaviors. Visual recognition techniques powered by AI, particularly deep learning models like Convolutional Neural Networks (CNNs), are able to process images or video footage of fish to automatically identify indications of disease. These models can be trained on labeled datasets containing both healthy and diseased fish images to distinguish between them. The automated identification of these visual symptoms allows for early disease detection, which is crucial for timely intervention and control of disease outbreaks. By detecting even subtle visual cues, these systems can contribute significantly to improving the health management of fish farms.

b. *Pattern Identification and Anomaly Detection*

AI algorithms can analyze vast amounts of data from various sources, such as environmental sensors monitoring water quality parameters (temperature, pH, ammonia levels, dissolved oxygen) and behavioral observations of fish (feeding patterns, swimming behavior). These systems utilize pattern recognition techniques to detect anomalies in the data, indicating potential health problems. For example, clustering algorithms or autoencoders can be employed to spot unusual patterns or deviations from typical fish behavior or environmental conditions. Such anomalies may signal early signs of disease or stress in fish populations, allowing for preemptive actions. Detecting these changes promptly is essential for mitigating the impact of diseases and ensuring the health of the farmed fish.

c. Expert Systems and Rule-Based Methodologies

Expert systems combine AI with expert knowledge in a particular domain to diagnose complex problems. In the context of fish health, expert systems integrate knowledge about various fish diseases, their symptoms, and the environmental factors associated with each condition. These systems use rule-based reasoning or decision tree algorithms to simulate the diagnostic process. By asking targeted questions about the observed symptoms (e.g., lesions, abnormal swimming patterns, etc.), the expert system can help users narrow down potential diagnoses and suggest appropriate treatments or preventive measures. This method bridges the gap between AI and expert knowledge, ensuring that disease detection is accurate and based on established scientific understanding. These systems are particularly useful for farmers and practitioners who may not have in-depth knowledge of specific fish diseases but can rely on AI-driven expertise to guide decision-making (Nagaraj and Deepalakshmi, 2022).

d. Support Vector Machines (SVM) and Classification Techniques

Support Vector Machines (SVM) and other classification algorithms are another set of tools used in fish health monitoring. These machine learning algorithms can classify fish into different disease groups by analyzing fish health data that includes a variety of input features such as water quality parameters, fish behavior, and molecular markers. The SVM model is trained using labeled datasets containing both healthy and diseased fish, enabling it to learn the distinguishing characteristics between different disease states. Once trained, the SVM can be used to analyze new data and classify fish accordingly, providing a fast and reliable means of diagnosing diseases. This approach allows for precise disease classification, which can inform subsequent decisions on treatment or control measures (González *et al.*, 2023). In addition to SVM, other classification techniques such as decision trees and random forests may also be employed to improve diagnostic accuracy.

e. Time-Series Analysis and Forecasting Models

Fish diseases, like many biological processes, often exhibit temporal patterns and trends. By using time-series analysis methods, such as Autoregressive Integrated Moving Average (ARIMA), Recurrent Neural Networks (RNNs), and Long Short-Term Memory (LSTM) models, AI systems can analyze historical health data to identify trends and predict future disease outbreaks. These methods are particularly effective for forecasting disease occurrences based on factors like environmental conditions (temperature, water quality), past disease events, and fish health data. The ability to predict disease outbreaks in advance provides aquaculture farmers with valuable lead time to implement preventive measures, reducing the potential impact of diseases on fish health and farm productivity. Time-series analysis also helps in understanding the seasonal variations in fish health, which is essential for adapting management practices accordingly (Arun Kumar *et al.*, 2022).

AI in Feed Management and Optimization

The integration of Artificial Intelligence (AI) in feed management has revolutionized aquaculture by enhancing feeding efficiency, minimizing waste, and optimizing fish growth. These advancements address economic challenges while promoting sustainable practices. AI applications in this domain leverage data analytics, machine learning, and automation to provide precise, science-driven *solutions for feed optimization*.

***a.* Optimizing Feed Formulation**

AI-driven optimization of feed formulation is transforming aquaculture nutrition by ensuring a balance between cost efficiency and fish health. Machine learning models analyze vast datasets, including nutritional requirements, ingredient availability, and cost constraints, to generate tailored feed formulations for specific fish species and growth stages. For example, predictive models assess the effects of protein, lipid, and micronutrient combinations on growth performance, feed conversion efficiency, and fish health. These formulations often consider local ingredient availability and alternative protein sources, such as insect or algal meals, to reduce dependency on traditional fishmeal and fish oil, contributing to sustainability (Glencross *et al.*, 2023). The use of AI ensures that nutritional adequacy is met while reducing production costs and environmental impacts.

b. Real-Time Monitoring of Feed Consumption

Real-time feed consumption monitoring using AI-based computer vision systems has significantly improved feeding precision. Cameras installed in aquaculture systems capture fish feeding behaviors, which are then analyzed using machine learning algorithms to quantify feed intake. These systems detect deviations in feeding activity, such as diminished appetite or irregular behavior, which may indicate health or environmental issues. By providing actionable insights, AI helps farmers fine-tune feeding strategies, ensuring that fish receive adequate nutrition without overfeeding. This reduces feed waste, improves feed conversion ratios (FCRs), and lowers nutrient loading in the aquatic environment, enhancing ecological sustainability (Zhang *et al.*, 2023).

c. Feeding Strategy Optimization

AI-enabled feeding strategies incorporate multiple factors, including fish size, growth stage, environmental conditions, and historical feeding patterns. Advanced reinforcement learning algorithms adapt feeding protocols dynamically, learning from real-time data to refine timing, quantity, and frequency of feed delivery. For instance, these systems can adjust feeding schedules during periods of suboptimal water quality, such as low oxygen levels or temperature fluctuations, to avoid metabolic stress. By continuously optimizing feed delivery, AI minimizes feed loss, improves growth rates, and ensures high FCRs, translating to better economic returns and reduced environmental footprints (Xia *et al.*, 2021).

d. Integrating Environmental and Feeding Data

AI enhances feed management by integrating environmental variables with feeding behavior and growth metrics. Machine learning models analyze data from sensors monitoring water temperature, pH, dissolved oxygen, and ammonia levels, correlating these with feeding efficiency and fish metabolism. This integration allows farmers to predict and mitigate adverse conditions that may impact feeding and growth. For example, during a sudden drop in oxygen levels, AI systems can recommend reduced feeding to prevent metabolic overload and stress. By providing holistic insights, these tools ensure that environmental sustainability aligns with growth optimization, fostering resilient aquaculture practices (Xia *et al.*, 2021).

e. Automating Feed Delivery Systems

AI-powered automated feeders have advanced aquaculture operations by combining real-time data acquisition with intelligent decision-making. These systems utilize sensor networks and predictive algorithms to dispense feed precisely based on fish behavior, biomass, and environmental parameters. For example, IoT-enabled feeders adjust feed volumes and schedules in response to real-time data on fish activity levels and water quality. Some systems incorporate AI models trained on historical data to predict feeding behavior under various scenarios, such as seasonal or diel cycles. Automation not only reduces manual labor and operational costs but also improves feed utilization, contributing to improved FCRs and minimized waste discharge into aquatic ecosystems.

Fig 3. AI-based Automatic Feed Delivery Systems in Aquaculture ponds

(Source: https://blog.pondking.com/)

Key AI Tools in Aquaculture

The integration of Artificial Intelligence (AI) with cutting-edge technologies such as the Internet of Things (IoT), machine learning, and automation has revolutionized the aquaculture industry. These tools enable real-time monitoring, data-driven decision-making, and the optimization of various farming operations. Below are some of the key AI tools transforming the aquaculture industry:

a. IoT in Aquaculture

The Internet of Things (IoT) has emerged as a critical enabler of precision aquaculture. By embedding sensors and connected devices within aquaculture systems, IoT facilitates continuous real-time monitoring of critical parameters such as water temperature, pH levels, oxygen concentration, and salinity. These devices collect vast amounts of data, which can be analyzed to optimize environmental conditions, track fish growth, and improve operational efficiency. For instance, IoT sensors can detect fluctuations in oxygen levels, triggering alerts that enable farmers to adjust aerators or pumps, maintaining optimal conditions for fish health. Additionally, IoT systems enhance farm management by monitoring the physical and chemical integrity of nets and tanks, helping to mitigate risks such as net wear or water contamination (Niswar *et al.*, 2018). The combination of IoT and AI allows aquaculture farms to adapt dynamically to changes in environmental conditions, including those caused by climate change, ensuring more sustainable and resilient farming practices. One example of such integration is Spain's OxyForcis system, which measures oxygen and temperature levels and provides real-time data through mobile devices, enhancing farm management (Martin, 2019).

b. AKVA Observe

AKVA Observe, developed by AKVA Global and Observe Technologies, is a pioneering software solution that enhances feeding efficiency in aquaculture systems. By utilizing AI, the system analyzes fish behavior, including feeding patterns and activity levels, and uses this data to optimize feed amounts and timing. The system employs visible pellet counting and behavioral analysis to ensure that the fish are fed the appropriate amount, reducing overfeeding and minimizing feed waste. This not only improves the feed conversion ratio (FCR) but also enhances fish growth, leading to increased productivity and cost efficiency. AKVA Observe is particularly valuable in large-scale farms, where manual feeding control can be cumbersome and inaccurate. By automating feeding and minimizing waste, this tool contributes to more sustainable farming practices, improving both the economic viability and environmental sustainability of aquaculture operations.

c. eFishery Smart Feeder

eFishery, an innovative Indonesian startup, has developed the eFishery Smart Feeder, a feeding system that uses AI to optimize feeding practices for fish and shrimp farming. The system relies on vibration-based sensors to detect the hunger levels of aquatic animals, ensuring that feed is dispensed only when needed. This intelligent feeding system has proven to reduce feed costs by up to 21% and increase harvest levels by 35%, making it a highly cost-effective solution. By tracking fish behavior and adjusting feeding schedules in real-time, the system prevents overfeeding, which can lead to wasted feed and increased environmental impact. The eFishery Smart Feeder can also be remotely monitored and controlled via an online dashboard, providing real-time updates on feeding schedules and allowing farmers to make adjustments as necessary. This tool exemplifies the benefits of AI-driven automation in optimizing resource utilization and maximizing farm profitability (Huzaifah, 2023).

d. FarmMOJO

FarmMOJO is an AI-driven mobile application designed to optimize shrimp farming operations by analyzing data from continuous pond monitoring. Developed by Aquaconnect, FarmMOJO helps farmers optimize feeding schedules, monitor water quality, and detect early signs of diseases, significantly improving farm efficiency. The app provides daily actionable recommendations based on the data it collects, including real-time water quality metrics such as dissolved oxygen, pH, and temperature, which are critical for shrimp health and growth. AI algorithms then analyze this data to suggest the optimal feeding strategies and alert farmers to potential issues such as disease outbreaks, which can be addressed before they become widespread. By improving feed conversion ratios (FCRs) and reducing operational costs, FarmMOJO enhances farm profitability and supports sustainable aquaculture practices (FarmMojo, 2019).

e. AquaCloud

AquaCloud is a powerful tool that brings together the expertise of fish health managers, researchers, and data scientists to track and analyze aquaculture data, facilitating better decision-making. This cloud-based platform integrates data from various sources, including IoT sensors, fish health monitoring systems, and environmental sensors, to provide real-time insights into farm performance. AquaCloud's advanced analytics capabilities help farmers optimize feeding practices, predict disease outbreaks, and manage environmental conditions more effectively. For example, the platform has been particularly useful in managing sea lice outbreaks by providing actionable data on fish health and environmental parameters. By merging data from different disciplines, AquaCloud enables data-driven decisions that enhance fish health and optimize farming practices, improving both sustainability and profitability in aquaculture.

f. Drones in Aquaculture

Underwater drones are increasingly being used in aquaculture for remote monitoring and management of fish farms. These drones are equipped with sensors that can measure key water quality parameters such as dissolved oxygen levels, temperature, salinity, and turbidity, offering valuable insights into the health of the farm environment. Additionally, drones can be used to inspect the condition of nets and other submerged equipment, providing real-time feedback to farmers. The ability to monitor farms remotely, particularly in harsh weather conditions, increases operational safety and reduces the need for manual labor. In the event of equipment damage or net degradation, drones can provide early detection, ensuring prompt repairs and minimizing the risk of farm losses (Orlowski, 2017). By enabling more efficient, safe, and comprehensive monitoring, drones contribute to better resource management and enhanced farm productivity.

g. Robotic Cages

Robotic cages, such as the Aquapod, represent an innovative advancement in the field of offshore

Benefits and Challenges of Using AI in Aquaculture

Benefits of Using AI in Aquaculture	Challenges of AI in Aquaculture
• Enhanced Efficiency: AI technologies streamline various processes in aquaculture, such as water quality monitoring, feeding schedules, and disease detection. This automation reduces the reliance on manual labor, improving operational efficiency and enabling farmers to manage larger operations with fewer resources.	• Availability and Quality of Data: The effectiveness of AI algorithms heavily depends on the availability and quality of data. Obtaining comprehensive and high-quality data can be challenging in aquaculture, particularly in remote or offshore environments. Poor-quality or incomplete data can lead to inaccuracies in AI models.
• Enhanced Decision-Making: AI systems analyze vast datasets to provide actionable insights that improve decision-making. By integrating data from sensors, satellites, and historical trends, AI helps optimize factors such as feeding schedules, water quality management, and overall fish health, contributing to better farm management.	• Insufficient Domain-Specific Data: AI models require domain-specific data for accurate training. In aquaculture, the lack of comprehensive datasets tailored to the sector can hinder the development of robust AI models. The process of gathering, annotating, and preparing these datasets is often resource-intensive and time-consuming.
• Early Detection of Diseases: AI can detect early signs of disease by analyzing fish behavior, physiological data, and environmental factors. This enables early intervention, preventing disease spread and reducing the risk of economic losses for farmers.	• Understanding Model Interpretation: Many AI models, particularly deep learning systems, are seen as "black boxes," making their decision-making processes difficult to interpret. In aquaculture, where decisions affect both fish welfare and economic outcomes, it is crucial to ensure transparency and interpretability in AI-generated recommendations to foster trust.
• Targeted Precision in Aquaculture: AI facilitates precision aquaculture by using real-time data to adjust variables like feeding, oxygenation, and water quality. These optimizations help enhance fish growth rates, feed conversion efficiency, and overall resource utilization.	• Expenses and Infrastructure Needs: Implementing AI technologies in aquaculture requires significant upfront investments in sensors, data collection systems, computational infrastructure, and skilled labor. This may present a barrier for small-scale or resource-limited farmers who find the costs and infrastructure requirements challenging.
• Sustainable Environmental Practices: AI contributes to sustainability by improving resource efficiency and minimizing the environmental footprint of aquaculture operations. Through data analysis of water quality, energy usage, and waste management, AI helps optimize operational practices to reduce ecological impact.	• Ethical Considerations: The use of AI in aquaculture raises several ethical issues, such as privacy concerns related to the collection and storage of sensitive data on fish health, farming practices, and market dynamics. It is important to ensure proper data protection, obtain informed consent, and use AI technologies responsibly in aquaculture applications.

aquaculture. These fully integrated systems include cameras, sensors, and automated feeding mechanisms, allowing for efficient fish farming in open ocean environments.The Aquapod and similar robotic cages are constructed using brass mesh to minimize biofouling and drag, reducing the need for regular cleaning and maintenance. This design enhances cage durability and operational efficiency, making it possible to farm fish in more challenging offshore locations. With real-time data collection on fish behavior, water quality, and feed consumption, robotic cages ensure optimal fish health and growth while minimizing human intervention. These systems are particularly suited for large-scale operations, where they enable continuous monitoring and efficient farm management even in remote locations (Mackowiak, 2019).

Conclusion

The integration of AI into aquaculture holds immense potential for transforming the industry by improving operational efficiency, enhancing decision-making, and promoting sustainable practices. Through the automation of critical tasks such as water quality monitoring, feeding optimization, and early disease detection, AI can significantly reduce manual labor, boost productivity, and minimize resource wastage. Furthermore, AI's capacity for analyzing complex data allows for precision management, improving fish health and growth rates while ensuring better resource utilization. While AI offers numerous benefits, challenges such as data availability, infrastructure costs, and the need for domain-specific knowledge must be overcome. Addressing these issues will require concerted efforts across research, industry, and policy-making sectors to foster an environment conducive to AI adoption. With ongoing advancements in technology and data collection methods, AI has the potential to drive more efficient, sustainable, and economically viable aquaculture practices, paving the way for a future of smarter and more responsible aquaculture systems.

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